1. A soft computing optimizer for designing a knowledge base to be used in a soft computing control of a motorcycle steering system, comprising:

a fuzzy inference engine;

a user input module configured to allow a user to select at least one optimization parameter, said optimization parameter comprising at least one of, a number of input variables of said knowledge base, a number of output variables of said knowledge base, a type of fuzzy inference model used by said fuzzy inference engine, and a preliminary type of membership function;

a dynamic simulation model of a motorcycle and rider;

a genetic algorithm configured to optimize said knowledge base using said fuzzy inference engine to control said dynamic simulation, said genetic algorithm configured to optimize said at least one optimization parameter.

2. The soft computing optimizer of Claim 1, wherein said fuzzy inference engine comprises a Fuzzy Neural Network.

3. The soft computing optimizer of Claim 1, wherein said fuzzy inference model comprises a Mamdani model.

4. The soft computing optimizer of Claim 1, wherein said fuzzy inference model comprises a Sugeno model.

5. The soft computing optimizer of Claim 1, wherein said dynamic simulation model comprises a feedfoward rider model.

6. The soft computing optimizer of Claim 1, wherein said genetic algorithm is configured to optimize said knowledge base according to a teaching signal.

7. The soft computing optimizer of Claim 1, wherein said dynamic simulation model comprises a linear tire model.

8. The soft computing optimizer of Claim 1, where said genetic algorithm optimizes a structure of said KB when said motorcycle is maneuvered along a circular path.

9. The soft computing optimizer of Claim 1, where said dynamic model is controlled by a linear controller.

10. The soft computing optimizer of Claim 1, where said genetic algorithm uses a fitness function configured to minimize a rate of entropy production of said dynamic model.

11. A method for optimizing a knowledge base in a soft computing controller for maneuvering a motorcycle, comprising:

selecting a fuzzy model by selecting one or more parameters, said one or more parameters comprising at least one of a number of input variables, a number of output variables, a type of fuzzy inference model, and a teaching signal;

optimizing linguistic variable parameters of a knowledge base according to said one or more parameters to produce optimized linguistic variables according to a teaching signal obtained from a dynamic simulation model of a motorcycle and rider;

ranking rules in said rule base according to firing strength;

eliminating rules with relatively weak firing strength leaving selected rules from said rules in said rule base;

optimizing said selected rules, using said fuzzy model, said linguistic variable parameters and said optimized linguistic variables, to produce optimized selected rules.

12. The method of Claim 11, further comprising optimizing said selected rules using a derivative-based optimization procedure.

13. The method of Claim 11, further comprising optimizing parameters of membership functions of said optimized selected rules to reduce approximation errors.

14. A soft computing optimizer, comprising:

a first genetic optimizer configured to optimize linguistic variable parameters for a fuzzy model in a fuzzy inference system;

a first knowledge base trained by a use of a training signal obtained from a dynamic simulation of maneuvering a motorcycle, said model including a tire model and a rider model;

a rule evaluator configured to rank rules in said first knowledge base according to firing strength and eliminating rules with a relatively low firing strength to create a second knowledge base; and

a second genetic analyzer configured to optimize said second knowledge base using said fuzzy model.

15. The soft computing optimizer of Claim 14, further comprising an optimizer configured to optimize said fuzzy inference model using classical derivative-based optimization.

16. The soft computing optimizer of Claim 14, further comprising a third genetic optimizer configured to optimize a structure of said linguistic variables using said second knowledge base.

17. The soft computing optimizer of Claim 14, further comprising a third genetic optimizer configured to optimize a structure of membership functions in said fuzzy inference system.

18. The soft computing optimizer of Claim 14, wherein said tire model comprises a linear tire model.

19. The soft computing optimizer of Claim 14, wherein said tire model comprises a linear tire model with transient effects.

20. The soft computing optimizer of Claim 14, wherein said second genetic analyzer uses a fitness function configured to reduce entropy production of the dynamic simulation model.

21. The soft computing optimizer of Claim 14, wherein said first genetic algorithm is configured to choose a number of membership functions for said first knowledge base.

22. The soft computing optimizer of Claim 14, wherein said first genetic algorithm is configured to choose a type of membership functions for said first knowledge base.

23. The soft computing optimizer of Claim 14, wherein said first genetic algorithm is configured to choose parameters of membership functions for said first knowledge base.

24. The soft computing optimizer of Claim 14, wherein a fitness function used in said second genetic algorithm depends, at least in part, on a type of membership functions in said fuzzy inference system.

25. The soft computing optimizer of Claim 14, further comprising a third genetic analyzer configured to optimize said second knowledge base according to a search space from the parameters of said linguistic variables.

26. The soft computing optimizer of Claim 14, further comprising a third genetic analyzer configured to optimize said second knowledge base by minimizing a fuzzy inference error.

27. The soft computing optimizer of Claim 14, wherein said second genetic optimizer uses an information-based fitness function.

28. The soft computing optimizer of Claim 14, wherein said first genetic optimizer uses a first fitness function and said second genetic optimizer uses said first fitness function.

29. The soft computing optimizer of Claim 14, wherein said second genetic optimizer uses a fitness function configured to optimize stability characteristics of the motorcycle.

30. The soft computing optimizer of Claim 14, wherein said second genetic optimizer uses a fitness function configured to optimize entropy properties of the motorcycle to steering control.

31. The soft computing optimizer of Claim 14, wherein said rider model comprises a look-ahead model.

32. The soft computing optimizer of Claim 14, wherein said second genetic optimizer uses a nonlinear model of the motorcycle and rider.

33. The soft computing optimizer of Claim 14, wherein a first linear controller is used to control steering and a second linear controller is used to control velocity.

34. The soft computing optimizer of Claim 14, wherein said teaching signal is obtained from an optimal control signal.

35. The soft computing optimizer of Claim 14, wherein said optimal control signal comprises a filtered measured control signal.

36. The soft computing optimizer of Claim 14, wherein said optimal control signal comprises a lowpass filtered measured control signal.

37. The soft computing optimizer of Claim 14, wherein said optimal control signal comprises a bandpass filtered measured control signal.

38. The soft computing optimizer of Claim 14, wherein said optimal control signal comprises a highpass filtered measured control signal.

39. A method for creating a knowledge base for a fuzzy inference system for controlling a motorcycle, comprising:

selecting first linguistic variable parameters that describe membership functions in said fuzzy inference system;

varying said first linguistic variable parameters in a first genetic algorithm to create optimized linguistic variables describing optimized membership functions for said fuzzy inference system;

creating a teaching signal from a dynamic model that describes a motorcycle steering and velocity;

creating a first knowledge base using at least said teaching signal and said optimized membership functions;

ranking rules in said first knowledge base according to a firing strength of each rule;

creating a second knowledge base from rules in said first knowledge base that have a relatively strong firing strength; and

using a second genetic algorithm to optimize said second knowledge base according to said optimized linguistic variables, said optimized membership functions, and said teaching signal to produce an optimized knowledge base.

40. The method of Claim 39, further comprising using a derivative-based optimizer to further optimize said optimized knowledge base.

41. The method of Claim 39, further comprising using a back-propagation algorithm to further train said optimized knowledge base.

42. The method of Claim 39, further comprising using a derivative-based optimizer to further optimize said linguistic variables.

43. The method of Claim 39, wherein said second genetic algorithm uses a fitness function configured to reduce entropy production.

44. The method of Claim 39, wherein steering of said motorcycle is controlled by a first linear controller and velocity of said motorcycle is controlled by a second linear controller and where said fuzzy inference system generates gain schedules for each linear controller.

45. The method of Claim 39, wherein said first genetic algorithm optimizes the number of membership functions in said fuzzy inference system.

46. The method of Claim 39, wherein said first genetic algorithm optimizes parameters of membership functions in said fuzzy inference system.

47. The method of Claim 39, wherein said teaching signal comprises one or more input signals and one or more output signals.

48. The method of Claim 39, wherein a history of activation of rules is associated with a history of activations of membership functions of output variables.

49. The method of Claim 39, wherein said fuzzy inference system comprises a Sugeno system and a history of activation of rules is associated with intervals of output signals.

50. The method of Claim 39, wherein said fuzzy inference system comprises a Sugeno system of order 0, and wherein intervals of the output signals are taken as a search space.

51. The method of Claim 39, wherein said second genetic algorithm depends, at least in part, on a type of said fuzzy inference system.

52. The method of Claim 39, wherein said second genetic algorithm uses an information-based fitness function.